Supplemental Material for

Virtual Raters for Reproducible and Objective Assessments in Radiology

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Supplementary Results

Label Statistics

In comparison to rater 1, rater 2 marked fewer voxels during the interactive labeling process. Rater 1 applied on average 12 brush strokes per volume with an average length of 9.9 voxels. Rater 2 used on average more brush strokes (20). However, these had a shorter length on average (4.2 voxels). Details are summarized in Table S2. Brush strokes were estimated using connected components.

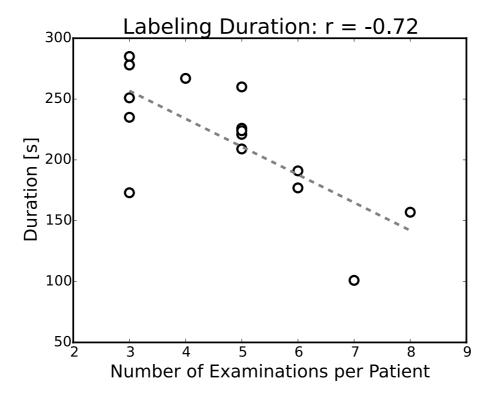


Figure S1: Relationship of annotation duration and number of follow-up scans. The more time points a 5D image data set of a patient contains, the less annotation time is needed on average during the proposed interactive workflow.

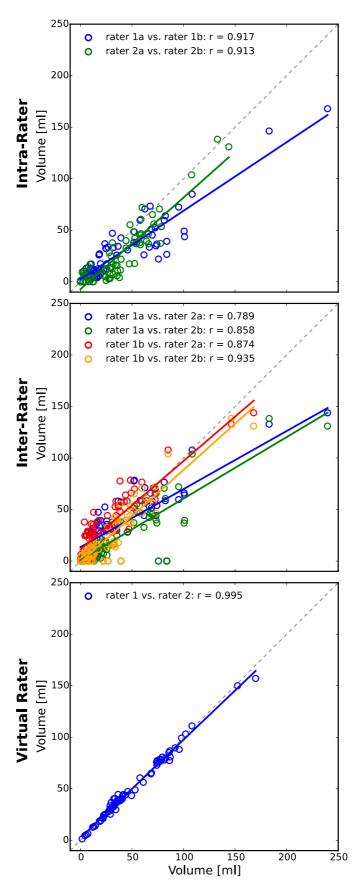


Figure S2a: Scatter plots showing intra-, inter- and virtual-rater Pearson correlation for the tumor edema category (N=71 MRI scans). All results are significant (p<<0.0001). The correlation for the virtual raters is higher than for the human experts.

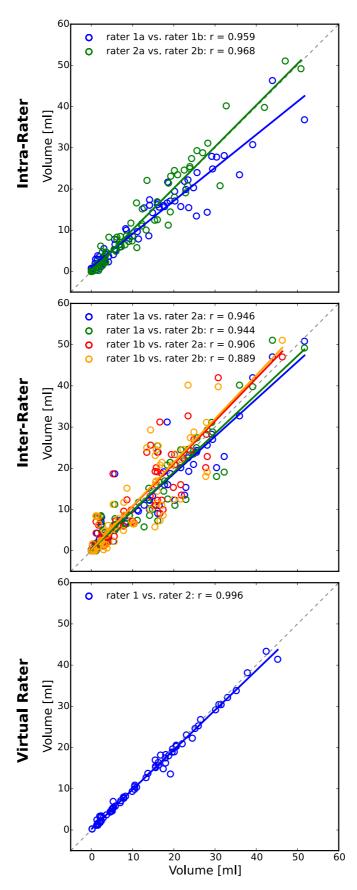


Figure S2b: Scatter plots showing intra-, inter- and virtual-rater Pearson correlation for the contrast-enhancing tumor category (N=71 MRI scans). All results are significant (p<<0.0001). The correlation for the virtual raters is higher than for the human experts.

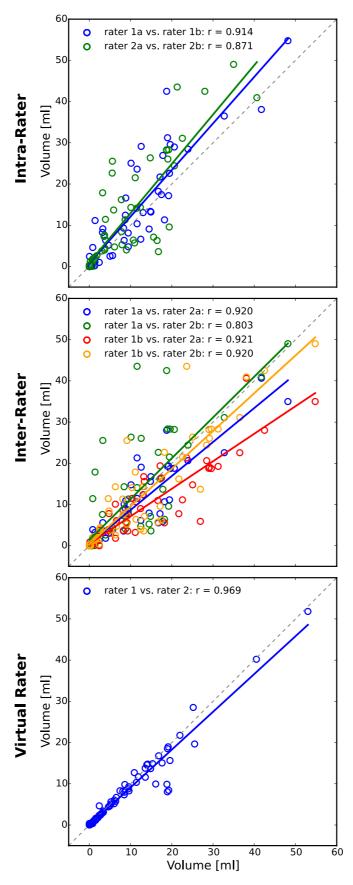


Figure S2c: Scatter plots showing intra-, inter- and virtual-rater Pearson correlation for the non-enhancing tumor category (N=71 MRI scans). All results are significant (p<<0.0001). The correlation for the virtual raters is higher than for the human experts.

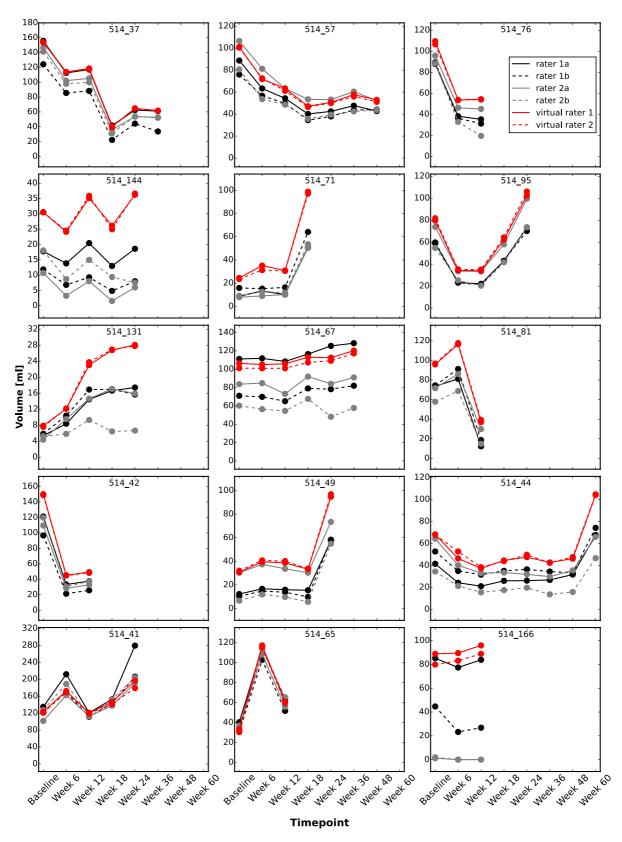


Figure S3a: Longitudinal GTV for 15 patients suffering from GB. The two human raters interactively segmented the tumor images twice (two independent sessions a and b). The virtual raters show a higher agreement amongst each other but in principle meet the assessments of the human experts.

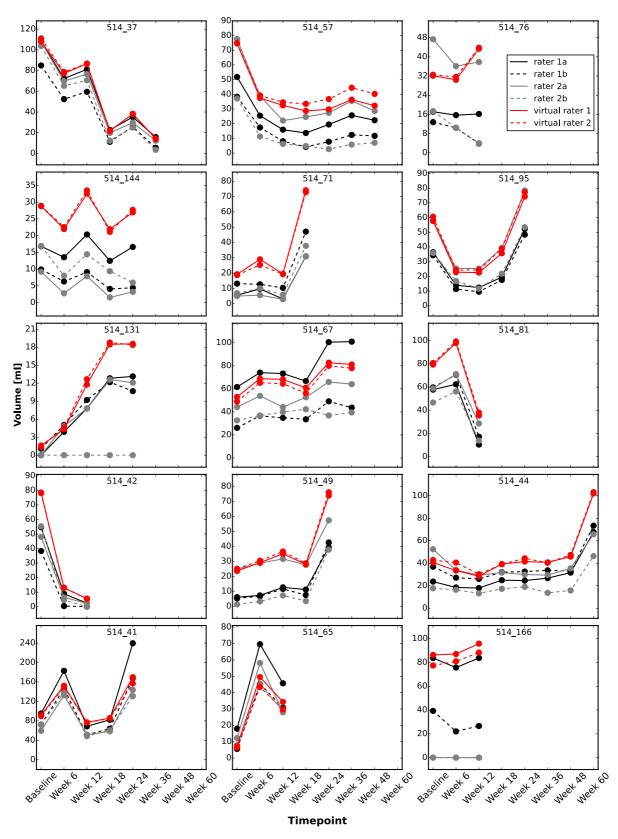


Figure S3b: Longitudinal tumor edema volume for 15 patients suffering from GB. The two human raters interactively segmented the tumor images twice (two independent sessions a and b). The virtual raters show a higher agreement amongst each other but in principle meet the assessments of the human experts.

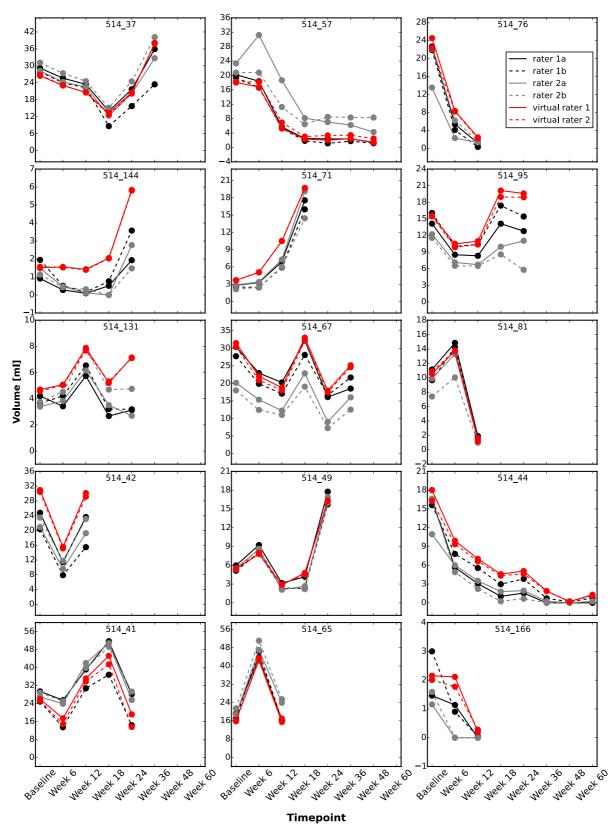


Figure S3c: Longitudinal contrast-enhancing tumor volume for 15 patients suffering from GB. The two human raters interactively segmented the tumor images twice (two independent sessions a and b). The virtual raters show a higher agreement amongst each other but in principle meet the assessments of the human experts.

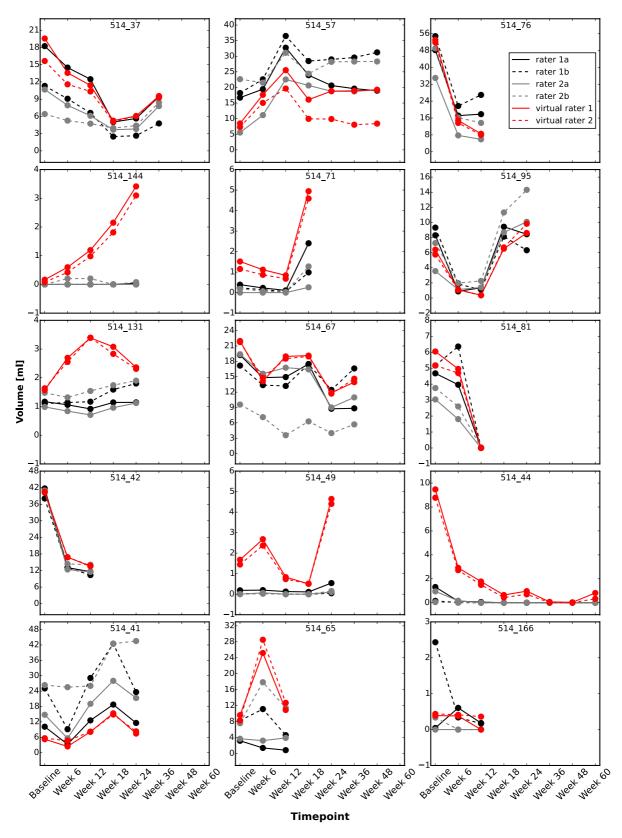


Figure S3d: Longitudinal non-enhancing tumor volume for 15 patients suffering from GB. The two human raters interactively segmented the tumor images twice (two independent sessions a and b). The virtual raters show a higher agreement amongst each other but in principle meet the assessments of the human experts.

Supplementary Tables

Table S1 – Labeling Duration and Tumor Volume Rater 1 $\,$

Dataset ID	Time	Combined Tumor	Average Tumor	Duration [s]	Average per
	Points	Volume [ml] of all	Volume [ml]		Time Point
		Time Points			[s]
541_37	6	398	66	1061	177
541_41	5	752	150	1103	221
514_42	3	144	48	519	173
514_44	8	332	42	1254	157
514_49	5	107	21	1046	209
514_57	7	343	49	708	101
514_65	3	185	62	703	235
514_67	6	445	74	1148	191
514_71	4	112	28	1079	267
514_76	3	157	52	856	285
514_81	3	185	62	752	251
514_95	5	217	43	1129	226
514_131	5	66	13	1299	260
514_144	5	41	8	1121	224
514_166	3	95	32	835	278

Table S2 – Label Statistics

			Category						
Type	Datan	Trial	Contrast-	Non-	T2	CSF	Rest	Air	
Type	Rater		Enhancing	Enhancing/	Edema				
				Core					
		a total	1503	860	2643	1217	2725	1141	
		b total	585	689	1139	938	1372	1431	
		a avg. (SD)	21 (20)	12 (20)	37 (36)	17	38	16	
	1					(18)	(44)	(27)	
	_	b avg. (SD)	8 (12)	10 (20)	16 (20)	13	19	20	
						(22)	(32)	(38)	
kels		Combined	15	11	27	15	29	18	
0		avg.					1.7.10	. =	
# of Voxels		a total	792	521	1436	1017	1540	1788	
#		b total	437	334	828	756	1179	1632	
		a avg. (SD)	11 (16)	7 (14)	20 (34)	14	22	25	
	2	1 (CD)	((0)	5 (10)	10 (04)	(26)	(30)	(48)	
		b avg. (SD)	6 (9)	5 (10)	12 (24)	(10)	17	23	
		Combined	9	6	1.6	(19)	(29)	(46)	
		Combined	9	6	16	12	19	24	
		avg.	1.47	90	156	100	240	<i>(</i> 1	
		a total b total	147 143	89 88	156 108	108 114	340 236	61 49	
							5 (4)		
	1	a avg. (SD)	2(2)	1(1)	2(1)	2(1)	3 (4)	1(1)	
es	1	b avg. (SD) Combined	2 (2)	1 (1)	2 (2)	2 (2)	3 (4)	1 (1)	
.ok		avg.	2	1	2	2	7	1	
Str		a total	361	177	186	127	798	72	
Brush Strokes		b total	317	138	97	80	529	60	
3ru		a avg. (SD)	5 (5)	2 (4)	3 (4)	2 (3)	11	1 (2)	
		ww.g. (32)		_ (.)	()	_ (0)	(11)	1 (-)	
	2	b avg. (SD)	4 (4)	2 (3)	1 (2)	1 (2)	7 (9)	1 (2)	
		Combined	5	2	2	1	9	1	
		avg.							
		a avg.	10.2	9.6	16.9	11.3	8.0	18.7	
Į.	1	b avg.	4.1	7.8	10.5	8.2	5.8	29.2	
ngt	1	Combined	7.2	8.8	14.3	9.7	7.1	23.4	
Stroke Length		avg.							
ke		a avg.	2.2	2.9	7.7	8.0	1.9	24.8	
tro.	2	b avg.	1.4	2.4	8.5	9.5	2.3	27.2	
S		Combined	1.8	2.7	8.0	8.6	2.0	25.9	
		avg.							

Table S3 – Leave-one-out cross validation of Dice scores with 1σ standard deviation. Categories that differ significantly (p<0.01) according to Welch's Two Sample t-test are denoted with an asterisk (*).

		Category									
		Contrast- Enhancing	Non- Enhancing/Core*	T2 Edema	CSF*	Rest	Air				
Human Raters	0.635 (0.191)			0.488 (0.245)	0.547 (0.188)	0.950 (0.045)	0.961 (0.102)				
Virtual Raters	0.636 (0.166)			0.486 (0.197)	0.463 (0.192)	0.958 (0.022)	0.968 (0.020)				

Table S4 – Welch's Two Sample t-test for comparison of GTV Dice Scores (BraTS data)

	Human Rater 1 vs. Human Rater 2
Virtual Rater 1 vs. Virtual Rater 2	t(35)=9.4, p << 0.00001
	Human Rater 1 vs. Human Rater 3
Virtual Rater 1 vs. Virtual Rater 3	t(33)=11.9, p << 0.00001
	Human Rater 1 vs. Human Rater 4
Virtual Rater 1 vs. Virtual Rater 4	t(33)=12.1, p << 0.00001
	Human Rater 2 vs. Human Rater 3
Virtual Rater 2 vs. Virtual Rater 3	t(33)=10.4, p << 0.00001
	Human Rater 2 vs. Human Rater 4
Virtual Rater 2 vs. Virtual Rater 4	t(35)=10.5, p << 0.00001
	Human Rater 3 vs. Human Rater 4
Virtual Rater 3 vs. Virtual Rater 4	t(33)=9.7, p << 0.00001

Table S5 – Mean inter-rater Dice scores with 1σ standard deviation

	Category								
	Gross Tumor	Normal	Necrosis	Edema	Non- enhancing tumor	Enhancing tumor	Air		
Human Raters	0.825 (0.069)	0.990 (0.008)	0.586 (0.303)	0.588 (0.280)	0.246 (0.303)	0.651 (0.286)	>0.999 (0.001)		
Virtual Raters P=1.0	0.963 (0.043)	0.998 (0.002)	0.743 (0.236)	0.922 (0.077)	0.685 (0.190)	0.825 (0.233)	>0.99 (0.001)		
Virtual Raters P=0.75	0.958 (0.053)	0.997 (0.002)	0.787 (0.200)	0.914 (0.090)	0.648 (0.219)	0.816 (0.252)	0.999 (0.001)		
Virtual Raters P=0.5	0.956 (0.060)	0.997 (0.002)	0.768 (0.235)	0.909 (0.091)	0.572 (0.268)	0.794 (0.265)	0.999 (0.002)		
Virtual Raters P=0.25	0.949 (0.078)	0.997 (0.002)	0.726 (0.278)	0.897 (0.106)	0.497 (0.290)	0.797 (0.265)	0.999 (0.002)		

Table S6 – Mean Dice scores compared to ground truth (reference segmentation) with 1σ standard deviation

		Category								
	Gross Tumor	Normal	Necrosis	Edema	Non- enhancing tumor	Enhancing tumor	Air			
Human Raters	0.899 (0.047)	0.994 (0.005)	0.726 (0.285)	0.746 (0.235)	0.431 (0.382)	0.741 (0.306)	>0.999 (0.001)			
Virtual Raters P=1.0	0.817 (0.097)	0.978 (0.010)	0.446 (0.313)	0.689 (0.149)	0.296 (0.260)	0.599 (0.337)	0.997 (0.002)			
Virtual Raters P=0.75	0.805 (0.109)	0.978 (0.009)	0.449 (0.321)	0.693 (0.157)	0.274 (0.263)	0.608 (0.333)	0.997 (0.002)			
Virtual Raters P=0.5	0.809 (0.108)	0.978 (0.010)	0.452 (0.319)	0.691 (0.155)	0.277 (0.269)	0.596 (0.331)	0.997 (0.002)			
Virtual Raters P=0.25	0.788 (0.168)	0.976 (0.010)	0.445 (0.319)	0.692 (0.162)	0.272 (0.289)	0.577 (0.343)	0.996 (0.003)			

Video Caption

Video 1: Demonstration of the MRIVolumetry Workflow. The exemplary use case illustrates a longitudinal brain tumor examination for a GB patient, including loading of 5D (time, x, y, z, channel) MRI-data, interactive annotation, filtering and report generation. The underlying machine learning algorithm captures the knowledge of the rater in close to real time.